Automated Vehicle Classification System Using Advanced Noise Reduction Technology

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***Abstract*— The demand for non-invasive vehicle counting and classifying devices has grown significantly in past decades due to contributing factors from occupational health and safety standards developed by state road authorities. In this paper, we present an automated vehicle classification system based upon the laser sensor technology. The system is capable of classifying vehicles in multi-lane, high speed environments, and requires no apparatus be placed on the carriageway. As opposed to the conventional Fourier-based filtering method, this paper also proposes a novel wavelet-based noise reduction technique to enhance performance.**

I. Introduction

Contemporary traffic engineers have long relied upon traffic surveys for collection of data. Most traffic control and design problems demand a fairly detailed knowledge of the operating characteristics of the traffic concerned, *e.g.*, traffic counts and classifications, speed surveys, vehicle dimensions, etc. [1], [2].

Extensive research in automated traffic surveys, produced by sensors either embedded in or above the road surface, have been conducted over past decades. Counting and classification systems developed from a wide variety of methods include pneumatic tubes, inductive loops, infrared traffic logger (TIRTL), radar, ultra sonic, video, etc. These counting systems can be generally classified into two distinct groups, namely, invasive and non-invasive systems. Invasive systems refer to the ones where sensors are installed within or upon the carriageway, whereas for non-invasive systems sensors are installed above or adjacent to the carriageway with no disruption to traffic flow [3].

The demand for non-invasive counting and classifying devices has grown significantly in past decades due to contributing factors from occupational health and safety standards developed by state road authorities. There is significant risk associated with departmental personnel working in proximity to high traffic volume environments.

In the paper, we discuss the development of a non-invasive automated vehicle classification (AVC) system based upon the laser sensor technology. The AVC system is capable of classifying vehicles in multi-lane, high speed environments, and uses an advanced wavelet-based noise reduction technique to enhanced performance. The remainder of the paper is organised as follows. Section II introduces the Austroads classification standard. Section III is dedicated to the universal laser sensor. Fourier and wavelet based signal noise reduction techniques are discussed in Section IV. The vehicle classification algorithm and experimental results are presented in Sections V and VI, respectively. Finally, concluding remarks are given in Section VII.

II. Austroads Classification Standard

An AVC system classifies vehicles into one of a number of distinct groups. It is usually applied in the disaggregation of traffic data, for example in the analysis and reporting of weigh-in motion data or the determination of annual average daily traffic (AADT). The current Austroads vehicle classification system, comprising 12 classes, has served well in its current form for the past five years [4].

The Austroads standard, updated in 1994 following Austroads project RUM.3.D.8 [4], is summarized in Table I. The standard determines the classes of vehicles based upon three levels, namely, length, axles and axle groups, and vehicle type.

TABLE I
Austroads vehicle classification system summary

Class	Description
1	Short vehicle
2	Short vehicle towing
3	Two axle truck or bus
4	Three axle truck or bus
5	Four axle truck
6	Three axle articulated
7	Four axle articulated
8	Five axle articulated
9	Six axle articulated
10	B-double
11	Double road train
12	Triple road train

A. Evaluation of existing sensor detector methods

We evaluate two typical sensor detector methods for designing AVC systems in this section. The first method called the pneumatic road sensor is currently the most common system used in Australia for counting and classifying vehicles. The sensor was invented in the 1920s as the first intrusive traffic detector technology. Due to its simplicity and low cost, the pneumatic road sensor is still widely in use today. Although the accuracy of the sensor is high, the pneumatic sensor system requires that technicians enter the carriageway to secure the sensors to the carriageway, exposing the workers to inherent dangers in high volume traffic environments.

The second method termed the infrared traffic logger (TIRTL) is a portable, light based vehicle counter, classifier and speed measurement device that measures vehicle axle breaks. The system consists of a pair of infra-red (IR) beam transmitter and receiver located on opposite sides of the carriageway. The system uses the order of timing of IR beams to determine the location and speed of passing vehicles. The TIRTL requires a receiver unit on the opposite side of the carriageway, so the installer may be exposed to road dangers.

B. *Laser Sensor Detector*

Due to the deficiencies of the two popular sensor detectors discussed in the preceding section, the laser sensor technology has been identified as the method for our AVS system. The laser sensing technology has the advantage of accuracy, and requires no human intervention for devise deployment and data collection. The laser sensor product we choose is the Universal Laser Sensor (ULS), manufactured by Laser Technology Incorporated [5].

III. Universal Laser Sensor

The ULS is a user-configurable distance measuring device. The ULS rangefinder sends a single laser pulse, typically 8ns in duration, to a target. The reflection from the target is then received by the sensor. It measures the time it takes for the pulse to return to the rangefinder. Since the speed of light is relatively constant across a large range of atmospheric conditions, the distance to the target can be calculated reliably.

The ULS allows adjustment of settings to optimize measurement performance depending upon the application. The device allows setting of the laser pulse firing rate frequency (PRF) ranging from 10 to 5000 Hz. To determine a distance to a target, the device averages the distance over a user defined number of pulses, which is termed pulses per measurement (PPM). This is because one individual pulse would not provide a very accurate measurement, since its travel time is too short (in the order of 10^{-12} seconds).

The measurement output data rate can be established as

$$R_o = \frac{\text{PPM}}{\text{PRF}}. \tag{1}$$

In our AVC system, we choose PRF $= 4000$, and PPM $= 16$. Therefore, the resulting measurement date rate $R_o = 0.004s$, implying a single measurement every 0.004 seconds or equivalently a measurement frequency of 250 Hz.

To achieve a higher output data rate, one can either decrease the PPM, or increase the PRF. Considering the case of a semi-trailer as shown in Fig. 1, where the grouped axles are considerably closer than in a passenger vehicle, there must exist sufficient laser pulses between axle detections in order to be able to distinguish between axles.

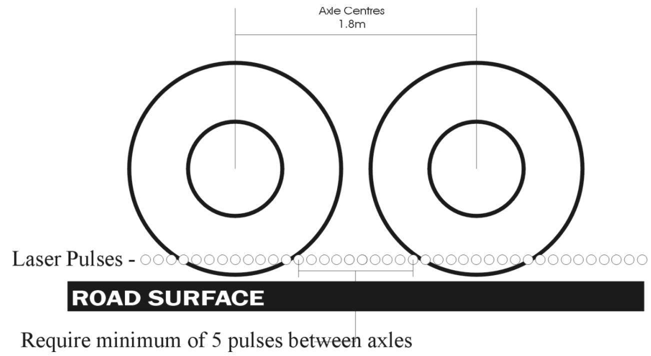


Fig. 1. ULS sampling of a typical semi-trailer axle group.

There is a trade-off between having a faster measurement rate with lower accuracy and a slower measurement rate with higher accuracy. For practical purposes, the measurement rate should be as low as acceptably possible.

In the proposed AVC system, two laser sensors were placed adjacent to the carriageway, approximately one metre apart. In order to be able to detect only axles, the laser must be low enough to the road surface so as to detect the wheels of the vehicle, but not the underside of the vehicle.

IV. Signal Noise Reduction Techniques

As mentioned in Section III, the AVC systems under consideration has a designed measurement frequency of 250 Hz. According to Nyquist Theorem [6], the system is able to reliably detect frequencies up to 125 Hz. Unfortunately, there is a considerable amount of noise in the measurement data due to the high PRF and low PPM parameters of the ULS. Moreover, the sensor signal output from the ULS is subject to severe additive white Gaussian noise (AWGN) when deployed in busy motorways. Therefore, advanced noise reduction techniques are imperative for developing the AVC system. Both Fourier and wavelet analysis methods for noise reduction are experimented and compared in this paper.

A. *Fourier-based Noise Reduction Technique*

Fourier analysis is widely utilised to remove noise in communications systems. One can use low pass filters to extract user information from noisy signals. The idea is to pass low frequencies but attenuate frequencies higher than a set cut-off frequency. Such a filter is normally specified in the frequency domain but designed in the time domain [6].

The Fourier-based noise reduction techniques is very effective if the noise presented in the laser sensor output is not time-varying. However, this is not always true as we observed from our field experiments. The major challenge of removing time-varying noise using low pass filters lies in the inherent problem of Fourier transform lacking adequate time resolution. This leads us to consider the application of advanced wavelet-based denoising techniques as discussed in the following section.

B. Wavelet Denoising Technique

It is observed that the laser sensor output may be corrupted by non-stationary noise resulted from time-varying traffic in motorways. Due to poor time resolution of Fourier transform, wavelet analysis is more suitable for removing such noise.

Unlike the conventional Fourier transform, whose basis functions are sinusoids, wavelet transforms are based on small waves, termed wavelets, of varying frequency and limited duration. This enables wavelet transform to reveal both frequency and temporal information of the signal being analysed.

A wavelet transform maps a time function into a two-dimensional function of a and t [7]. The two parameters, a and t, represent scale and translation respectively. The continuous wavelet transform (CWT) is mathematically defined as [8]

$$W_\psi(a,t) = \frac{1}{\sqrt{a}} \int s(t)\psi\left(\frac{t-\tau}{a}\right) dt, \qquad (2)$$

where $\psi(t)$ is the mother wavelet. Conversely, if the mother wavelet $\psi(t)$ is invertible, the inverse transform can be defined as

$$s(t) = \frac{1}{C_\psi} \int_{-\infty}^{\infty} W_\psi(a,t) \frac{1}{\sqrt{a}} \psi\left(\frac{t-\tau}{a}\right) \frac{1}{a^2} da\, dt, \qquad (3)$$

where a is a positive number, and C_ψ is a constant.

For discrete signals, however, one can not directly apply (2) due to the fact that the calculation of this transform requires an infinite amount of data. Mallat proposed an efficient method to implement the discrete version of the wavelet transform [9]. The Mallat algorithm is graphically illustrated in Fig. 2

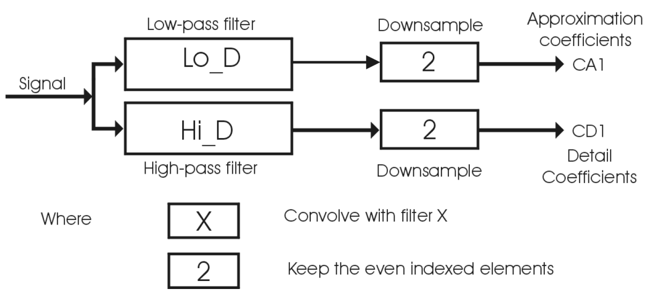
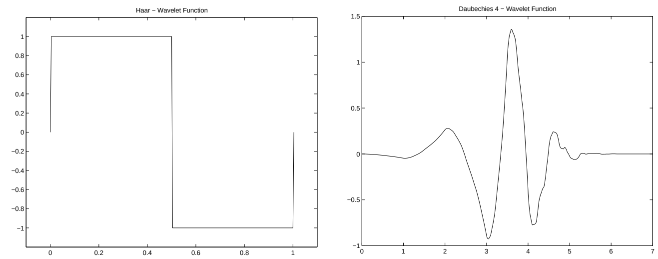


Fig. 2. Mallat wavelet decomposition.

As can be seen from Fig. 2, the input signal is convolved with both a high pass and a low pass filter, producing two arrays of coefficients twice the size of the original signal. Downsampling is performed upon each array of coefficients, keeping only the even numbered coefficients. The signal is now separated into two discrete frequency bands. CA represents the approximation coefficients, *i.e.*, the lower frequency coefficients, whereas CD represents the detail coefficients, *i.e.*, the higher frequency coefficients.

The strength of wavelet transform representations is that signals that have similar features to the wavelet function at any scale may be well represented by only a few of the wavelet basis functions. As different families of wavelets have different properties, the choice of the mother wavelet must be carefully considered.



(a) Haar 1 wavelet function (b) Daubechies 4 wavelet function

Fig. 3. Haar and Daubechies wavelet functions.

Figs. 3(a) and 3(b) illustrate two popular wavelet functions, *i.e.*, Haar wavelet and Daubechies wavelet. The Haar wavelet function resembles the ideal noise-free laser sensor signal, which has very sharp edges indicting the transition from no axle present to an axle present. As a result, we choose the Haar wavelet function as the mother wavelet for our wavelet denoising scheme.

Wavelet denoising of a signal involves computing the discrete wavelet transform of the signal and then decreasing or discarding the smallest wavelet coefficients. The inverse transform of these coefficients will then be a filtered version of the signal. More specially, wavelet denoising can be ordered into three steps. First, decompose the signal to a level of N using the selected mother wavelet. Second, detail coefficients thresholding: for each level from 1 to N, select a threshold and apply thresholding to the detail coefficients. Third, reconstruct the signal based upon the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N. The second step is the most critical one, which largely determines the performance of the wavelet filter.

V. Vehicle Classification Algorithm

In order to classify vehicles, a number of parameters are required. These parameters are then used to determine the vehicle and their appropriate classes. According to the Austroads standard, the classifying system bases classification upon combinations of four parameters, namely, number of axles, number of axles groups, axle spacing of first and second axles, and axle spacing of second and third axles if it exists.

There is a specific sequence of events that the classification algorithm uses to successfully count and classify vehicles detected by the AVC system. The events can be summarised into the following ordered processes

1) Load the sensor output file containing the measured data;
2) Denoise data from both lasers using wavelets;
3) Calculate the position of each lane relative to the sensors;
4) Separate vehicles into particular lane for analysis;
5) Select the first lane to classify;
6) Detect axles in the current lane;
7) Determine speed of the first axle in data;
8) Calculate axle spacings at axle speed;

9) Select axles, until axle spacing exceeds 10m as part of current vehicle;
10) Determine the number of axles and axle groups in current vehicle;
11) Determine separation of first and second axles;
12) Determine separation of second and third axles if it exists;
13) Continue determining individual vehicle data for particular lane;
14) Increment to the next lane;
15) Go back to Step 6) and repeat the classification process until the last lane.

A couple of crucial techniques in the classification process are explained in more detail in the following subsections.

A. Axle Detection

Edges characterise the boundaries of leading and trailing edges of wheels of the vehicle, and are therefore a problem of fundamental importance in processing the signal. Edge detecting significantly reduces the amount of data and filters out useless information, while preserving the important structural properties of the signal.

Edge detection algorithms can be divided into two major categories, *i.e.*, methods using Gradient and Laplacian filters [6]. The Gradient filter uses the first derivative to find changes in amplitude of the signal. Peaks in the Gradient filtered signal indicate edges in the original signal. The Laplacian filter uses the second derivative to find changes in the first derivative. The Laplacian method can be used to find edges in the original signal by finding the zeros crossings in the Laplacian filtered signal.

A positive peak identified by the axle detection algorithm indicates the leading edge of the wheel, and a negative peak indicates the trailing edge. Typically, only the leading edges of the wheels will be required, from which the distance between axles can be calculated.

B. Axle Grouping

An axle is defined as part of a group if the distance to an adjacent axle is less than 2.1 metres. The distance between axles is found easily from the detection of the front edge of the wheel. The time between the first positive peak produced from the gradient filter on Laser 1 and the first positive peak on Laser 2 is taken as the time the vehicle took to travel from Laser 1 to Laser 2. Since the distance between the two lasers is known to be one metre, the speed of the vehicle can be easily calculated as $v = d/t$.

Once the speed of the vehicle is known, this distance between consecutive axles can be found from edge detections on one set of the laser data. The spacing between consecutive axles is calculated by multiplying the time between edges by the speed of the first axle. When the distance between axles exceeds the Austroads standard of 10m for maximum axle spacing, the remaining axles in the data are not considered to be part of the current vehicle.

VI. EXPERIMENTAL RESULTS

In this section, we present our testing procedure and experimental results for the AVC system we propose. We first present the comparative results between Fourier-based and wavelet-based noise reduction techniques.

Fig. 4 demonstrates the application of a low pass filter to a real laser sensor output signal. The original noisy signal is shown as the dotted line. As can be seen from Fig. 4, ringing is produced before and after any axle event, further complicating axle detection, whilst the noise is attenuated well between axle events. The filtered signal peaks have been attenuated substantially. While the original signal shows the vehicle at approximately 1.5 metres from the sensor, after filtering the signal, the vehicle ranges from four to five metres from the sensor. This makes the lane identification unreliable, and further discredits the use of a low pass filter in the system.

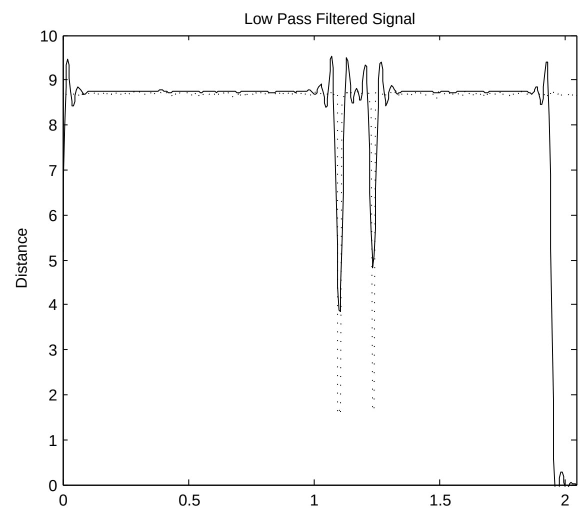


Fig. 4. Denoising of real sensor output using a low pass filter.

Fig. 5 demonstrates the result of applying a wavelet filter to a real laser sensor output signal. The data was denoised using six levels of decomposition. As compared with the results in Fig. 4, it is evident that the Haar wavelet denoising technique offers much better noise reduction performance for this particular application, and is therefore chosen as the method for denoising the measurement data in the classification algorithm.

To evaluate the performance of our AVC system, a field testing procedure has been developed. The objective of the testing procedure is to determine the accuracy at which the developed system can detect axles and calculate the axle separation of known vehicles.

Both single-lane and multi-lane scenarios are considered in the testing procedure. Fig. 6 shows the layout for the multi-lane scenario. For this configuration, field experiments were conducted on Bridge Street in Toowoomba, Queensland, a single direction, double lane uncontrolled environment, where the existing speed limit was 60 km/hr. Video footage of the

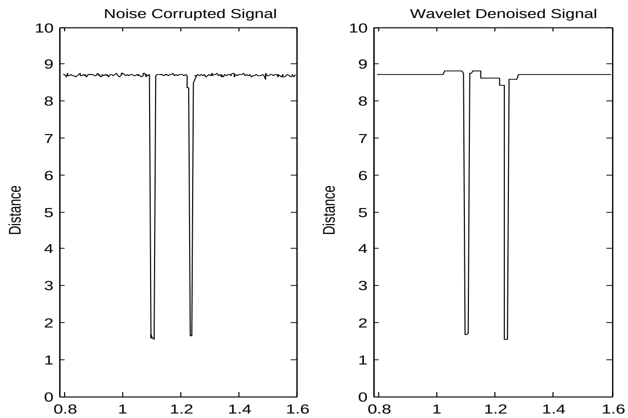


Fig. 5. Denoising of real sensor output using a wavelet filter.

passing vehicles was recorded so as to later compare the vehicle types determined by the system with vehicle types visually observed.

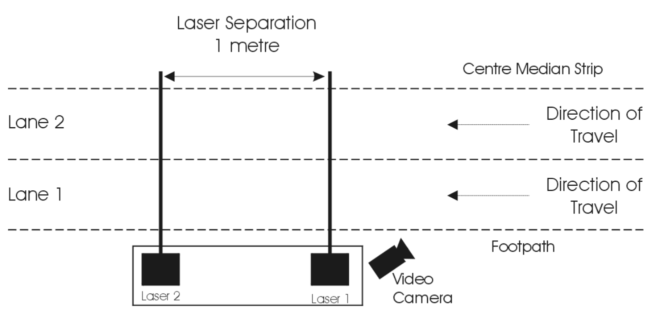


Fig. 6. Multi-lane test procedure layout.

Table II shows the first 20 classified vehicles of a 57 vehicle classification sample. 39 of the 57 vehicles in the classification sample were classified successfully. Of the 39 vehicles that classified successfully, the speed of each vehicle appears to be marginally high.

For the misclassified vehicles, the visual inspection indicated that nearly all misclassified vehicles were the larger wheel base type vehicles such as four wheel drive utilities. These vehicles tend to have wheel bases closer to the the limit of 3.2 metres between class 1 and class 3 classification. The incorrect determination of speed would cause the vehicle to be determined to have a longer wheel base if the speed was recorded too high. It should be noted that speed inaccuracy, which is responsible for misclassification, is largely due to the synchronisation problem between two laser sensors when date is being reading out from them. It appears that the only solution to this problem will be via the use of two designated processors for reading out data from each of the sensors simultaneously. Our future work will address this issue.

TABLE II

AUSTROADS VEHICLE CLASSIFICATION SYSTEM TEST RESULTS

Vehicle Number	System Classification	Visual Classification	Speed (km/hr)
1	Class 1	Class 1	69.2
2	Class 1	Class 1	75.0
3	Class 1	Class 1	90.0
4	Class 1	Class 1	75.0
5	Class 3	Class 1	75.0
6	Class 1	Class 1	75.0
7	Class 1	Class 1	64.3
8	Class 3	Class 1	100.0
9	Class 3	Class 1	100.0
10	Class 1	Class 1	75.2
11	Class 3	Class 1	90.0
12	Class 3	Class 3	75.0
13	Class 1	Class 1	81.8
14	Class 3	Class 1	69.2
15	Class 1	Class 1	69.2
16	Class 1	Class 1	75.0
17	Class 3	Class 1	75.0
18	Class 3	Class 1	90.0
19	Class 3	Class 1	90.0
20	Class 9	Class 9	69.2

VII. CONCLUSIONS

In this paper, we discussed the development of an automated vehicle classification system for the Austroads standard based upon the laser sensor technology. A novel wavelet-based noise reduction technique was also proposed to enhance the system performance. The concept of using laser sensors as a replacement for pneumatic tubes, which are currently used for vehicle classification in Australia, has been proved.

The system is truly non-invasive in the fact that it requires only that the sensors be deployed on one side of the carriageway. There is no requirement for technicians to enter the carriageway, and the system does not affect motorists. This aspect of the system will have a positive impact on injuries sustained by staff setting up traffic count sites. The future development of this work will lead to commercially viable AVC products.

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